# DETECTION OF FINANCIAL STATEMENTS FRAUD USING BENEISH AND DECHOW MODELS

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## Abstract

Fraudulent financial reporting is a big issue not only for investors but also for other stakeholders. This research uses two popular fraud detection models by Beneish (1997, 1999a) and Dechow et al. (2011). The main goal of this paper is to compare the precision of these two models for the prediction of fraud in the financial statements of Iranian companies. Firstly, we try to identify the statistical description related to the first and fourth quartiles of the Beneish and Dechow models. Then, we determine the models' forecasting capabilities using SPSS software by t-test and variance analysis. We use the sample of 197 companies during the 11-years period from 2009 till 2019. The results indicate that the Beneish model has more precision and less error level in fraud detection in the financial statements than the Dechow model. The general precision of the Beneish model, with 83%, compared to the Dechow model, with general precision of 75%, demonstrates the volume of fraud in the company's financial statements. According to the statistical results, the prediction precision of the Beneish model, compared to the Dechow model, is more, and its estimation error is less than the latter. Therefore, according to this hypothesis, the Beneish model enjoys a higher detection power in the probability of committing fraud in the financial statements than the Dechow model. Thus, in companies with a previous record of earnings management, there is the probability of committing fraud in the financial statements. It is possible to detect fraud more easily by the Beneish model. The findings of Beneish (1999b) research, Jones et al. (2008), Dechow et al. (2011), and Perols and Lougee (2011) confirm the result obtained from this hypothesis.

**Keywords:** Beneish Model, Fraudulent Financial Reporting, Dechow Model, Disclosure of Information

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## 1. INTRODUCTION

Fraud detection in the finance system is essential to ensure financial stability and risk management and create insurance conditions for all market participants. Trust is the foundation of finance. Science must help practitioners detect all possible fraudulent activities to protect financial markets

from high volatility and financial system from problems of financial stability. Fraud in finance is related not only to institutional issues but also to many consequences for retail investors. Fraud problems are analyzed in scientific papers using different techniques and tools, but suitable methods for different countries and markets remain open. Achmad et al. (2022) tried to detect fraud in financial statements using Fraud Hexagon analysis in the Indonesia Stock market from 2016 to 2020.

Despite the techniques of detecting fraudulent activities are improving. Still, the number of increasing fraud cases in the companies and the negative consequences on market players encourages scientists to analyze this topic again using different tools. Vousinas (2019) created a new model including stimulus, capability, opportunity, rationalization, and ego. Wyrobek (2020) for fraud detection, applied machine learning, and artificial intelligence techniques.

The U.S. Securities and Exchange Commission (SEC) requisites concerning the detailed investigation of detecting earnings manipulations have created a strong incentive for the research. However, there is minimal scientific and professional literature for identifying earning manipulation. In the accounting literature, earnings management and earnings manipulation are not differentiated, while their differentiation should be described. Kaplan (1968) introduces the relative capability of decreasing or increasing the directors' reported earnings as manipulation in the accounts (Mashayekhi et al., 2005). Earnings manipulation refers to the intentional actions of the company's directors to approach the reported earnings to the ideal level, which is classified into three groups: earnings management, fraud in earnings, and creativity in accounting, given conformity with the accounting rules and standards. Earnings management refers to the earnings manipulation in the frame of accounting standards and corporate rules not negatively affect the company's value. Because of execution, earnings manipulation could be in the form of manipulation in the accruals, manipulation in real items, and manipulation in the earnings fluctuations (smoothing).

Fraud in earnings is the extremist form of earning manipulation in which the directors violate the Generally Accepted Accounting Principles (GAAP) and commit accounting offenses. Fraud in earnings could result in the devaluation of the company by changing the structure of the company's operations. Creative accounting is an earnings manipulation occurring due to the weakness or absence of standards and rules in a particular issue. Therefore, it does not violate accounting standards and corporate rules (Esfahani & Saghafi, 2012).

However, the accepted attitude in the earnings manipulation studies is the explicit and implicit contracts between the beneficiaries and the company, which could provide various incentives for the directors to manipulate financial information (Pourheydari & Hemmati, 2004).

The techniques of earnings management and fraud in earnings are different. In earnings management, the directors select accruals and real items based on the GAAP, but in fraud, they use methods to violate GAAP. Methods of fraud in profit are more extremist than the earning management in utilizing the accruals and real items. Therefore, the difference between earning management and fraud in earning is utilizing legal and illegal methods to alter figures in financial statements (Rosner, 2003).

However, Dechow et al. (2011) believe earning manipulation is performed in and out of the GAAP. They explain earning management in the scope of GAAP could prevent the potential legal expenses incurred due to earning manipulation out of the GAAP (fraud in earning). Therefore, managers are expected to use earning management to cover fraud in earnings.

Accordingly, developing a model to identify such offenses is essential (Dechow, 1996). Beneish (1999b) used a model based on the eight accounting variables to detect earning manipulation. He found an unusual increase in the claims, a decrease in gross profit margin, decreased quality of assets, growth in sales, and increased accruals. The probability of earning manipulation increases. His findings indicate the usefulness of accounting information for detecting earnings manipulation. The Beneish model as a fraud prediction tool was also analyzed by (Sabău (Popa) et al., 2021) using a sample of Romania companies.

We expand the research by analyzing the Beneish model and adding the Dechow model to predict earning manipulation in Iran companies that participate in the stock market. We expand on the cientific study by Shakouri et al. (2021) adding the Dechow model and applying two models from 2009 till 2019. The main research question is as follows:

*RQ: Which model, Beneish or Dechow, predicts fraud in Iranian companies better?*

This research's main objective is to compare the precision of two models to predict earning manipulation of Iranian companies. Beneish and Dechow models are not new methods for detecting fraud, but this research aims to identify which model is a better predictor for Iranian companies. We add value to the literature by comparing these two models, and at the same time, we give practical insights for investors and analysts who care about earnings manipulation. This topic is very relevant because we need more suitable tools for predicting fraud in stock markets. Fraudulent information about one company can significantly negatively affect other companies. Spillover effects can be powerful and destroy trust in financial markets. This is the main reason which encourages us to analyze these models and identify which one can help to identify manipulations in a better way.

The research hypothesis is following:

*H1: The Dechow model has a higher fraud detection capability than the Beneish model.*

The structure of this paper is as follows. In Section 2, we present a literature review. Section 3 provides information about the methodology we have used. The results of the paper are presented in Section 4 and discussed in Section 5. The study is concluded in Section 6.

## 2. LITERATURE REVIEW

An essential factor in earning management tests in companies is the estimation of the authority factor

and the directors' decision in the earning determination. A review of earning management-focused literature indicates the existence of different approaches with different indicators in the estimation and measurement of management authority in determining the reported earnings. One of the most important approaches is applying *discretionary accruals* as an index for determining and detecting earning management in business units.

Siregar and Utama (2008) used three types of benchmarks for the assessment of the future in this research: 1) net profit of non-discretionary accruals; 2) cash flow of operational activities; 3) net profit. They also used changes in net profit due to the inherent weaknesses of net profit.

Healy (1985), DeAngelo (1986) and Jones (1991), presented models during studies on earning management through the application of accruals to detect earning management, which was repeatedly tested in further research. Dechow et al. (1996) presented a model, later called the "modified Jones model", and compared it with Jones (1991), Healy (1985), and DeAngelo's (1986), and the industry models. They concluded that the modified Jones' model could detect earning management in the business units.

The role of accruals in the performance of companies is a topic of accounting that has been studied for years. Still, there is no consensus if the directors use the accruals for this autonomy or transformation of other helpful information from the earning reports to benefit the flexibility provided by GAAP. Asymmetry of information among the directors of profit units and individuals out of the company leads the directors to use accruals to transfer the company's information to the users through the financial reports. Chung et al. (2004) found evidence in a study indicating that the stock market affects the pricing of discretionary accruals, and discretionary accruals predict future returns.

Jones (1991) identified the difference between earnings and cash amounts earned from the operations as the *accruals*. In this approach, the information on the cash amounts earned from the operations is a more objective criterion for the assessment of the fundamental economic performance of the business unit, and thereby, it is less likely to be manipulated by the management. In the model presented in 1991 for the review of earning management in the business units, Jones (1991) assumed that non-discretionary accruals are fixed throughout time. In this model, trying to separate discretionary and non-discretionary accruals, it is tried to control the impact of economic conditions of a business unit on the nondiscretionary accruals. Dechow et al. (1996) presented a modified form of the Jones model. They believed that the Jones' model implicitly assumes that income items, neither at the estimation of model parameters (event period) nor at the estimation of earning management (estimation period), are altered and manipulated by the management. They violated the assumption and believe the sale (income) changes during the estimation period originated from the earning management. Numerous studies focused on the review of incentives for earning management. Since earning manipulation is very similar to earning management, much research has been done in this field. Dechow et al. (1996) believed earning manipulation could be elaborated through the incentives of earning management, such as the bonus and external financing hypotheses. Dechow et al. (1996) demonstrated that debt could result in earning manipulation, mainly when the loan contract includes typical conditions. Risk aversion of the lender causes the inclusion of a typical debt contract, and directors manipulate earnings to encounter it using accruals. Earning manipulation occurs when the directors select the accrual and actual items in and out of GAAP and employ accounting. Utilization from the accruals in the scope of GAAP is deemed as earning management for covering fraud. Earning manipulation often occurs in organizations with weak management structures and debit limitations, which require external financing.

Earning manipulation models include accrual-based and combined financial ratios and accruals. Utilization of directors from the accruals models to detect earning manipulation earning management type is valid. Although the accruals provide the possibility of earning manipulation, they also significantly impact the evaluation of a company's performance. When the directors use both accruals and actual items in and out of GAAP for the manipulation, the combined models have a better performance for detecting this type of earning manipulation. Therefore, accruals models are often used to detect earning management and the combined models to detect earnings management and fraud. Healy (1985) was the first researcher who introduced accruals-based models, and then DeAngelo (1986) and Jones (1991) improved them with different methods and names. Dechow et al. (1995) modified the Jones' model. The modified Jones' model implicitly assumes that change in the credit sale is caused by manipulating financial information. Thus, the Jones' (1991) model deducted changes in claims from changes in credit sales to calculate non-discretionary accruals. Beneish (1997) was first who introduced the combined models of earnings manipulation, then Spathis (2002) followed him. The role of accruals in the performance of companies is a topic of accounting that has been studied for years (Nugroho et al., 2022; ElHawary & Hassouna, 2021; Burdeos, 2021; Fera & Salzillo, 2021; Kalantonis et al., 2021).

The research study on the reviewed variables provides a higher insight for the researchers to evaluate earning management. Brazel et al. (2009) studied the number of inventions, employment, production, and their impact on revenue growth. They concluded that fraudulent companies have more differences in revenue growth and nonfinancial changes than other companies. Since accruals management is cheaper than a change of accounting method and operational cash flow and has stealth capability, earning management is mainly accomplished through manipulating accruals. Thus, researchers are increasingly using the variables of accruals to detect earning management.

Beneish M-score and Dechow F-score are unique and utilize an extensive scope of financial variables, (including the sale, profit margin, lever, obligations, and others), to detect factors of potential earning. Both models are built with an analysis of

the standard features of ambiguous companies. The variables of this models are selected for tracking the accounting alterations caused by the manipulation. Like the Altman's bankruptcy prediction model, both models give a score to the company, which could be a red flag for the earning management. Both scores are quickly calculated because they need the fiscal year's data. The M-score model needs data from two fiscal years, and F-score needs data from three fiscal years to evaluate manipulation possibilities. Therefore, both models are used to identify companies' situations. Beneish M-score model was received after declaring Enron's company disreputable before bankruptcy (Beneish et al., 2012).

Namazi and Ebrahimi (2017) accomplished research with the title modeling and prioritization of factors effective on the intention of the report of financial frauds by the accountants. In this research, the effect of factors of organizational justice, attitude towards reporting, personal cost of reporting, active personality trait, purity, and moral severity has been studied. The results of the hypothesis using regression of the ordinary least square (OLS) method indicates that the variables of organizational justice, attitude towards reporting, active personality trait, purity, and moral severity have a positive and significant impact on the intention of an internal report of fraud cases. In contrast, the impact of the reporting variable's personal cost is insignificant. The estimated research model indicates that organizational justice, moral severity, and attitude towards reporting have the highest impact on reporting fraud items in the financial items. The results of this research report that the *theory of organizational justice* has the potential to participate in implementing effective mechanisms for reporting fraud cases. Moreover, to increase the efficacy of mechanisms implemented to promote the report of fraud cases, attention to the activities, like implementing morality training programs and cultural and religious programs, could positively impact purity and attitude is critical.

Kordestani et al. (2016) reviewed earning manipulation: development of a model in Iran. For this purpose, the authors examined the data of 90 manufacturing companies (990 observations) admitted in the Tehran Stock Exchange in 2002–2012 with the help of a distinguished attitude and Logit. The findings indicate that in the economic environment in Iran, the initial Beneish model does not have good power for detecting levels of earning manipulation compared to the modified Beneish model. The adjusted Beneish model and the developed models with an attitude of discriminant analysis and Logit, respectively, with general precision of 72%, 75%, and 81%, can detect the companies manipulating and non-manipulating earnings. Moreover, the evidence demonstrated that accounting information is useful for predicting earning manipulation.

In their study, Rezaei and Jafariniaraki (2015) investigated the correlation between tax avoidance and accounting fraud in companies. The study's findings revealed a direct and significant relationship between tax avoidance and accounting fraud in companies when using the effective rate of cash tax and permanent tax difference as benchmarks for tax avoidance. However, when tax avoidance was evaluated based on the long-term effective rate of cash tax, no significant relationship was observed between tax avoidance and accounting fraud in companies.

Farajzadeh Dehkordi and Aghaei (2015) conducted a comprehensive examination of the relationship between dividend policy and fraudulent financial reporting over the period from 2002 to 2011. The study's results revealed that companies that distributed dividends were less likely to engage in fraudulent financial reporting. Additionally, there was a negative correlation between the level of distributed dividends and the occurrence of fraudulent financial reporting. Based on these findings, it was concluded that dividend policy contains valuable information about the quality of a company's financial reporting, particularly regarding the incentives that might lead to restating financial statements.

Aghghaleh et al. (2016) reviewed the detection of financial fraud in Malaysia in a study: they compared the capabilities of the Beneish and Dechow models, and after review of companies registered in Malaysia from 2001 to 2014, they concluded that both Beneish and Dechow models are effective in the prediction of two methods of fraud. The precision of models was respectively 73.17% and 76.22%. The results also demonstrated the F-score Dechow model is superior to the Beneish M-score model because of its sensitivity to the prediction of fraud cases with 73.17%. This finding indicates that the Dechow model is superior. Franceschetti and Koschtial (2013) reviewed the Beneish model in a sample of 30 bankrupt companies and 30 non-bankrupt companies. They found that in bankrupt companies, earnings are manipulated and decrease significantly one year before the bankruptcy.

Lennox et al. (2013) studied the relationship between tax reporting fraud and accounting fraud. Relying on several criteria for tax avoidance, including the effective tax rates and permanent tax differences, and the SEC report regarding the fraudulent companies. Their results imply that the fraudulent company has less likely to tax avoidance. In other words, the companies with tax avoidance commit fraud in accounting less likely. Their conclusion was emphasized when they separated the period 1995–2001, in which non-qualification of accounting increased rapidly, and the acceptable tax of companies decreased rapidly. They argued that companies with fraud in their financial reports try to have less tax avoidance, reduce external supervision, and reduce the probability of fraud detection.

Impink (2010) studied the impact of earning manipulation on the continuation of activity and bankruptcy of Worldcom Co. during 2000–2001. He used the Beneish (1999) model for the prediction of earning manipulation and the Altman (1968) model, and the Ohlson (1980) model for the prediction of bankruptcy. His findings indicated that earning manipulation is related to the continuation of activity and bankruptcy criteria. Kirkos et al. (2007), using financial ratios as the input variables and applying data mining methods, reviewed the fraud detection procedure in financial statements.

Decision tree (DT), artificial neural network (ANN), and Bayesian network (BN) models reported prediction accuracy rates of 96%, 100%, and 95%. The results indicate the ability of fraud detection through the data of financial statements. Abbott et al. (2000) accomplished research on the effects of the activities of audit committees and independence on fraud of big companies and reviewed and measured the independence of auditing and activity in decreasing the probability of fraud. Using logistic regression analysis, they found that companies with an audit committee, with a combination of non-executive boards of directors and at least two times per year meetings, have less tendency to decide fraudulent or delusive reporting decisions. Spathis (2002) analyzed the prediction of manipulating financial information (fraud in earnings) using the financial ratios of 76 companies admitted in the Athene Securities Stock Exchange and the logistic regression method. He found that the proportion of inventory to sale, debt to asset, and the Altman Z-score model have the explanatory power to manipulate financial information.

## 3. METHODOLOGY

This research is applied type given objective and correlative type given nature. The research has a deductive-inductive approach, and among the types of correlation research is regression analysis. Moreover, since the data used in this research are real and historical information, it could be classified as ex post facto.

The location scope of research is the companies admitted in the Tehran Stock Exchange, which are considered suspected of fraud based on one of the fraud factors of study by Forghandoust Haghighi et al. (2014).

The period used in this research is 2009–2019. In this research, the systematic deletion method is used for the sampling. For this purpose, all companies of the statistical population during the study period with one of the fraud factors of study by Forghandoust Haghighi et al. (2014) are selected as a sample, and the rest are deleted.

Since the Association of Certified Fraud Examiners (ACFE) (2016) defines financial reporting type fraud as false presentation and or intentional omission of the basic and significant items of accounting information deceptively, resulting in change and or adjustment of decision and judgment of readers of financial statements. A series of factors related to the false and deceptive presentation of accounting information in financial reporting has been used to select the companies suspected of fraud in the financial statements. In this study, the method of Forghandoust Haghighi and Barvari (2010) is used for selecting the companies suspected of fraud in the financial statements. In this method, it is assumed that the companies that, during the examined period, audit reports have been rejected, have no remark, or have been conditional, have a higher probability of committing fraud than the companies with an accepted audit report. Therefore, the companies whose audit reports during the examined period have been rejected, have no remark or have been conditional, are identified. Then, among the identified cases, the companies that in their audit report, one of the following instances of fraud mentioned as the reason of their remark, upon proving one of the instances, are identified as the company suspected of fraud. The first five cases were selected based on the research of Maher et al. (2007), Forghandoust Haghighi and Barvari (2010), Vakilifard et al. (2009), Hosseini (2011), and Forghandoust Haghighi et al., 2014, which are: 1) improper identification of incomes and improper measurement of realized in-comes; 2) overstatement of assets and inventories at the end of the period; 3) improper identification of expenses and lack of measurement of realized expenses; 4) understatement of debts and improper and deceptive utilization from the reserve accounts; 5) lack of preparation of financial statements, assuming suspension of companies activities which assumption of the continuation of their activity is basically under question and reflected in the audit reports. Furthermore, the sixth instance, based on section 24 of accounting standards in Iran, is an improper application and non-observance of the procedures, estimation, and Accounting Accepted Standards related to the assessment, identification, classification, presentation, or disclosure of significant items in the financial statements (Forghandoust Haghighi et al., 2014).

In this research, the period from 2009 to 2019 is studied. The companies suspected of fraud have been admitted to the Tehran Stock Exchange before 2009. Their shares were transacted in the stock exchange from March 21, 2009. Moreover, all required information of the companies was available, and the mentioned companies were not included in the number of the investment, financial intermediary, leasing, monetary and financial firms. Considering the above terms and limitations, 197 companies suspected of fraud were selected, and the research hypothesis was tested using the data companies during 2009–2019.

According to the theoretical basis and research background, the research hypothesis presented above was formulated.

To obtain the required variables related to the financial statements of the examined companies, we referred to the financial statements provided in the electronic archive of the Tehran Stock Exchange.

A part of the required information was obtained from the popular software of the database of Tadbir Pardaz and Dena Sahm. The information was extracted from the latest revised standards of accounting.

### 3.1. Beneish model

The Beneish (1999b) model, also known as the M-score, is a financial fraud detection model developed by Prof. Messod D. Beneish. The model uses a combination of eight financial ratios to identify the likelihood of financial manipulation or earnings manipulation in a company's financial statements. It is primarily used by analysts and investors as a tool to assess the integrity and reliability of a company's financial reporting. The eight financial ratios used in the Beneish model are presented in the table below.

**Table 1.** Components of Beneish M-score

| *Variables* | *Description* | *Measurements* |
|---|---|---|
| *DSRI* | Days' sales in a receivable index | Measures the increase in receivables relative to sales |
| *GMI* | Gross margin index | Measures the change in gross margin ratio |
| *AQI* | Asset quality index | Evaluates the increase in non-current assets relative to total assets |
| *SGI* | Sales growth index | Measures the change in sales |
| *DEPI* | Depreciation index | Evaluates the decrease in depreciation relative to sales |
| *SGAI* | Sales and general and administrative expenses index | Measures the increase in selling, general, and administrative expenses relative to sales |
| *LVGI* | Levitt's index | Assesses the increase in leverage relative to the previous year |
| *TATA* | Total accruals to total assets | Measures the change in non-cash accruals relative to total assets |

By calculating the M-score, which is a weighted sum of these eight ratios, the Beneish model provides a numerical value that indicates the likelihood of earnings manipulation. A higher M-score suggests a higher probability of manipulation, while a lower M-score indicates a lower probability. It is important to note that the Beneish model is a statistical tool and should be used as part of a comprehensive analysis. It does not guarantee the presence or absence of fraud but serves as an indicator to highlight companies that may warrant further investigation.

The tested coefficients of the model are:

$$M = -4.84 + 0.92 * DSRI + 0.528 * GMI + 0.404 * AQI + 0.892 * SGI + 0.115 * DEPI - 0.172 * SGAI + 4.679 * TATA - 0.327 * LVGI \quad (1)$$

In this model, the breaking point was obtained at 0.5. Therefore, if the calculated score (*M-score*) exceeds 0.5, the company most probably manipulates the earnings. Beneish measures the relative figures of the companies and obtains the threshold value of -1.78. This means that if the result of a company is higher than this value, the potential risk of earning manipulation is high (Beneish, 1999b).

## 3.2. Dechow model

The Dechow model, also known as the Dechow and Dichev (2002) model, is a financial accounting model that focuses on predicting earnings quality and the likelihood of earnings manipulation in a company's financial statements. The model primarily uses accruals-based measures to assess the quality of reported earnings.

The Dechow model examines a company's accruals and cash flows to identify potential red flags that may indicate earnings manipulation. It considers two main components:

1. *Discretionary accruals:* Accruals are non-cash accounting entries made to recognize revenues and expenses that have not yet been realized. Discretionary accruals refer to those accruals that management can potentially manipulate to influence reported earnings. The model estimates discretionary accruals by regressing the current period accruals on factors such as sales growth, working capital changes, and depreciation changes.

2. *Non-operating activities:* These are transactions or events that do not directly relate to a company's core operations. These activities can sometimes be used to manipulate earnings. The model examines non-operating activities, such as gains or losses from asset sales, to assess their impact on reported earnings.

By analyzing these components, the Dechow model provides a quantitative measure that indicates the likelihood of earnings manipulation. A higher model score suggests a higher probability of earnings manipulation, while a lower score indicates a lower probability.

It's important to note that the Dechow model, like the Beneish model, is a statistical tool that serves as an indicator and should be used alongside other financial analysis methods. It provides insights into potential earnings quality issues, helping investors and analysts make more informed decisions and identify companies that may require further investigation.

$$Predicted\ value = -7.90 + 0.790 * RSSTACC + 2.518 * CHREC + 1.191 * CHINV + 1.979 * SOFTASSETS + 0.171 * CHCS - 0.932 * CHROA + 1.029 * ISSUE \quad (2)$$

The predicted value does not show the probability of alteration. Rather, this figure should be placed in the final formula to find the probability of earning alteration. The final formula is:

$$\frac{e^{predicted\ value}}{1 + e^{predicted\ value}} * \frac{1}{0.0037} \quad (3)$$

Selected variables for the probability of an increase in earnings management are listed in Table 2 below.

**Table 2.** Components of Dechow model

| *Variables* | *Description* | *Measurements* |
|---|---|---|
| *RSSTACC* | Change in net non-cash operational assets | $\frac{Change\ in\ net\ non\text{-}cash\ operational\ assets}{Total\ assets}$ |
| *CHREC* | Change in receivable accounts. | $\frac{Change\ in\ receivable\ account}{Average\ total\ assets}$ |
| *CHINV* | Change in inventory | $\frac{Change\ in\ inventory}{Average\ total\ assets}$ |
| *SOFTASSETS* | Intangible assets | $\frac{Intangible\ assets}{Average\ total\ assets}$ |
| *CHCS* | Change in cash sale | $\frac{Sale_t - Change\ in\ receivable\ account_t}{Sale_{t-1} - Change\ in\ receivable\ account_{t-1}}$ |
| *CHROA* | Change in asset return | $\frac{Earning}{Average\ total\ assets}$ |
| *ISSUE* | If the company has issued a share certificate is 1, and otherwise, 0. | |

This statistic (*F-score*) is 1.00 at maximum. It indicates that the company has not altered earnings; if it exceeds 1.00, it implies a high statistical probability of earning alteration. Finally, we could conclude the more results of these tests, the higher probability of earning alteration.

SPSS 21 software was used at an inferential level to respond to the research hypotheses, single sample t-test, and t-test of two independent samples.

## 4. RESULTS

### 4.1. Descriptive statistics and models assessment

In this part, the descriptive statistics of variables used in the research are reviewed and presented in Table 3. The values represent just a general scheme of the distribution of research data.

The descriptive statistics of discretionary accruals' first and fourth quantiles are as follows.

**Table 3**. Descriptive statistics of discretionary accruals

| *Parameters* | *No* | *Minimum* | *Maximum* | *Mean* | *Std. deviation* |
|---|---|---|---|---|---|
| *ABDA* $q_1$ | 197 | 0.000706 | 0.060947 | 0.030717 | 0.018264 |
| *ABDA* $q_4$ | 197 | 0.114075 | 38.941534 | 0.432744 | 2.770805 |
| Valid N (listwise) | 197 | | | | |

*Note: ABDA = absolute value of discretionary accruals; q1 = first quantile; q4 = fourth quantile.*

Table 3 shows the results of descriptive statistics, that is, the statistical indexes of mean, standard deviation, minimum and maximum. The mean of accruals is 0.03 in the first quantile and 0.43 in the fourth quantile. The standard deviation is 0.018 in the first quantile and 2.77 in the fourth quantile.

Descriptive statistics of the Dechow and Beneish models are as follows (Table 4):

**Table 4**. Descriptive statistics of Dechow and Beneish models

| *Parameters* | *No* | *Minimum* | *Maximum* | *Mean* | *Std. deviation* |
|---|---|---|---|---|---|
| *M-score* $q_1$ | 197 | -8.125871 | -2.099966 | -3.362037 | 1.167551 |
| *M-score* $q_4$ | 197 | -2.089101 | 17.815630 | -0.008380 | 3.262618 |
| *F-score* $q_1$ | 197 | 0.002682 | 0.128944 | 0.091273 | 0.031600 |
| *F-score* $q_4$ | 197 | 0.226529 | 5.569452 | 1.456196 | 0.575181 |
| Valid N (listwise) | 197 | | | | |

Table 4 shows the results of descriptive statistics, that is, the statistical indexes of mean, standard deviation, minimum and maximum. Concerning the statistics of the Beneish model in the companies with manipulation probability of -0.008 and mean Beneish index in the control companies is -3.36. The mean of Dechow statistics in the companies with a probability of manipulation is 1.45 and 0.092 in the control companies. The above figures indicate that the company classification has been done correctly.

To test the research hypothesis, the precision of two models in prediction is estimated based on the number of manipulated companies estimated by two Beneish and Dechow indexes and a comparison with the real number of companies with a probability of sample manipulation, and similarly in the control companies.

The precision of the two models is checked through the test of two models for six actual fraudulent companies condemned to fraud by issuing finalized judiciary verdicts for the companies in the list of the Tehran Stock Exchange for reasons related to data alteration and performing concealed transactions.

The prediction accuracy and precision of two models in two examples with the possibility of manipulation and control group are presented in Table 5 and Table 6. Dechow model has a higher capability in fraud detection than the Beneish model.

**Table 5**. Results of assessment precision of Beneish model ($M \leq -1/78$)

| *Group* | *Observations* | *Precision* | *Error* | *Correction prediction* | *Wrong prediction* |
|---|---|---|---|---|---|
| Non-fraudulent | 171 | 169 | 2 | 98% | 1.16% |
| Fraudulent | 26 | 25 | 1 | 96% | 3.8% |
| General precision of model | | (169 + 1) / 197 * 100 = 86% | | | |
| General error of model | | (2 + 25) / 197 * 100 = 13% | | | |

*Note: General precision = (fraudulent precision + non-fraudulent precision) / number of fraudulent + number of non-fraudulent) * 100; General error = (fraudulent error + non-fraudulent error) / (number of fraudulent + number of non-fraudulent) * 100.*

**Table 6**. Results of assessment precision of Dechow model

| *Group* | *Observations* | *Precision* | *Error* | *Correction prediction* | *Wrong prediction* |
|---|---|---|---|---|---|
| Non-fraudulent | 184 | 163 | 21 | 88% | 11.41% |
| Fraudulent | 13 | 10 | 3 | 76% | 23% |
| General precision of model | | (163 + 3) / 197 * 100 = 84% | | | |
| General error of model | | (21 + 10) / 197 * 100 = 15% | | | |

*Note: General precision = (fraudulent precision + non-fraudulent precision) / number of fraudulent + number of non-fraudulent) * 100; General error = (fraudulent error + non-fraudulent error) / (number of fraudulent + number of non-fraudulent) * 100.*

### 4.2. Test of two models in the real example of fraudulent companies

Based on the test results till now, both models could detect the probability of fraud in the companies admitted to the Tehran Stock Exchange.

To check the precision of the two models, an example consisting of six companies admitted to the Stock Exchange condemned to fraud by issuing finalized judiciary verdicts, performing concealed transactions, and non–submission of clear information to the Tehran Stock Exchange are investigated by the two models. In addition, six non-fraudulent listed companies similar to the test group in terms of size (normal logarithm of assets) are tested as controls for the two models.

**Table 7.** Results of precision of models assessment

| *Situation* | *Dechow model (predicted values)* | | *Beneish model (predicted values)* | |
|---|---|---|---|---|
| Observations/prediction | Non-fraudulent | Fraudulent | Non-fraudulent | Fraudulent |
| Non-fraudulent | 5 | 1 | 5 | 1 |
| Fraudulent | 2 | 4 | 1 | 5 |
| Prediction precision in percent | 83% | 67% | 83% | 83% |
| Total | 75% | | 83% | |
| Alpha-type prediction error (non-identification of fraud for the fraudulent company) | 33% | | 17% | |
| Beta-type prediction error (identification of fraud for the nonfraudulent company) | 17% | | 17% | |

The results in Table 7 indicate that the Beneish model has a higher precision coefficient and less error percentage. So, considering the results.

Based on the results of the above tests, the null-hypothesis ($H_0$) is accepted, and *H1* is rejected.

The statistics of two models of the probability of fraud, based on the items extracted from the financial statements of Iran Counter Manufacturing Co., which left the stock exchange in 2016 due to the fraud in the financial statements, are presented in Table 8.

**Table 8.** The results of the two models in 2015

| *Model* | *Values* |
|---|---|
| Dechow model | 0.456944 |
| Beneish model | -1.32784 |

As you can see, the Dechow model could not declare fraud, but the Beneish model has declared the necessary alarm for fraud.

## 5. DISCUSSION

Nowadays, companies' insolvency, fraud, and failure have always been complicated and noteworthy issues. In the present world, unlimited human desires face limited economic resources. Any event's appearance and fall originate from human societies' natural and logical needs. The appearance of fraud auditing in professional services is not excluded from this rule. Technological progress and extensive changes in the business environment have led to an increasing acceleration in the economy. Due to firms' increasing completion, the expected earnings achievement is limited. Thus, the conditions for fraud occurrence are increasing. Fraud is any planned, intentional action, omission, and deletion to deceive or seduce others. It causes its victims to suffer loss and the doers and of-fenders to receive interest.

From any culture, religion, or other feature, all society members are subject to the temptation of committing fraud. According to International Standard on Auditing (ISA) 240, fraud is any intentional action by one or more executive directors, leadership members, staff, or third parties containing deception for the enjoyment of an unfair or illegal advantage. Fraud in the financial report could destroy the company's report, so the company's nature may be risked. As per Fraud Act (2006)[1] applies in England, Wales and Northern Ireland, fraud includes deceit for personal interest and or loss for the other. Many attempts have been made to assess the actual volume of fraud, but collecting reasonable statistics is not easy. Most

[1] https://www.cps.gov.uk/legal-guidance/fraud-act-2006

fraud cases are not detected, and even when it is detected, they may not be reported, but the company victim of the fraud does not want to have a damaged honor among the public. The increase in fraud in financial reporting and the cases of representation of financial statements, often combined with the insolvency of big companies, has led to concerns about the quality of financial reporting. On this account, the investors, legislators, directors, and auditors have always focused on preventing or defecting significant fraud in financial reporting.

Considering the significance of financial fraud in the economy, followed by the enormous losses for the shareholders and society, many financial frauds are not detected or disclosed for any reason. Generally, contrary to the advanced countries with an organization for detecting financial fraud, there is no firm, organization, or documented information concerning fraud in Iran. Thus, paying attention to the fraud in the financial statements and reviewing its practical factors could help us. The auditor's negligence or failure occurs when the auditor has not applied the most miniature precision, which should apply according to the standards. Negligence violates the minimum requirements, and the auditor is directly responsible for its consequences. Delinquency occurs when the auditor does not observe the reasonable level of care and vigilance expected from a professional auditor. A reasonable level of care and vigilance is provided through the utilization of auditors' judgment and in the frame of the probability of risk, significance, and situation of internal controls structure. It is mainly near the high limit of care instead of mini-mums, and the auditor is responsible for such special conditions.

The intention and purpose of deception always accompany the term fraud. It occurs when the auditor presents the type and content of its report unreally with the intention and purpose of deception (mainly with management's cooperation). A synonym for 'fraud' in the judiciary procedures related to the courts held against the auditors is 'negligence' which is generally defined as the "equivalent of fraud", and the punishment of fraud is considered negligence. In recent years, fraud in companies has cost huge expenses millions. Just in the United States and England, the reported frauds amount to billions of dollars, although it is believed such reports included just 10% of total frauds. The evidence implies that fraud in companies is a serious problem. Such frauds, particularly when the directors and senior staff of companies commit them, usually appear when they are unexpectedly involved in cute problems. In such cases, the question arises that where the auditors have been. The role of independent auditors in detecting and reporting fraud in companies is controversial. The professional remarks of auditors are different, and thereby, to reduce expectations from the auditing performance, the utmost cooperation is necessary. Numerous reviews have reported that while politicians, courts, financial publications, and many others expect auditors to detect and report fraud, the auditing profession has generally reduced its responsibilities in this respect and emphasizes that fraud detection is the responsibility of directors.

## 6. CONCLUSION

According to the statistical results, the prediction precision of the Beneish model, compared to the Dechow model, is more, and its estimation error is less than the latter. Therefore, according to this hypothesis, the Beneish model enjoys a higher detection power in the probability of committing fraud in the financial statements than the Dechow model. Thus, in companies with a previous record of earnings management, there is the probability of committing fraud in the financial statements. It is possible to detect fraud more easily by Beneish model. The findings of Beneish research (1999), Jones et al. (2008), Dechow et al. (2011), and Perols and Lougee (2011) confirm the result obtained from this hypothesis.

Taking into account the significance of the subject and research findings that were referred to, it is suggested that users of financial statements and organizations supervising them, like internal and independent auditors and inspectors, consider that a previous record of earnings management could be an alarm for the probability of management fraud.

In the case of a record of earnings management, incentive factors will act as a stimulus for committing fraud. Forming the triangle of fraud factors increases the probability of committing it. Thus, the auditors aware of a record of earnings management in the examined company are suggested to plan and implement their methods and tests considering the increase in the probability of commitment of management fraud in the financial reporting.

In addition to the above suggestions, the final model of this research can predict the probability of fraud in financial reporting through the capability of risk evaluation and assessment of altered financial statements and render service to the supervisor, approver, and user groups of the financial statements.

To prevent fraud in their companies, the company's directors should enhance their performance and not put the company in inappropriate and stressful conditions.

Considering a significant relationship, the auditors are recommended to pay particular attention to these two models when checking the significance level when auditing companies.

The financial and credit firms and investors are recommended to consider the Beneish model to estimate loan and investment risk.

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